Multi-Class Banana Leaf Disease Detection via KHO-YOLOv8

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Research Article

Keywords: Banana disease detection, Sigatoka Negra, Deep Learning, YOLOv8, Krill Herds Optimization

Posted Date: June 4th, 2025

DOI: https://doi.org/10.21203/rs.3.rs-6812770/v1

Additional Declarations: The authors declare no competing interests.

Multi-Class Banana Leaf Disease Detection via KHO-YOLOv8

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Abstract

Plant diseases initiate major agricultural challenges because they lead to 16\% of worldwide crop loss in farms. The vulnerability of bananas to diseases including Xanthomonas Wilt and Sigatoka leaf spot puts severe threats to food security because of their extensive damage potential. These diseases possess the risk of damage to the complete harvest so their impact can reach 100%. While deep learning models, particularly YOLO-based architecture, have demonstrated success in plant disease identification, key research gaps remain. One major challenge is the lack of large-scale, annotated datasets for banana leaf diseases, limiting the development and evaluation of robust AI models. Addressing these challenges is crucial, and this study aims to do so by creating a large dataset and developing a robust disease detection model. The dataset comprises more than 5000 samples categorized into three classes: Healthy, Xanthomonas Wilt infected, and Sigatoka leaf spot infected. This study examines a novel framework by employing advanced optimization techniques such as Krill Herd Optimization (KHO) for YOLOv8 and its variants. Our research findings highlight the exceptional performance of the KHO-YOLOv8 model, achieving an impressive accuracy of 96.47%.

Keywords: Banana disease detection, Sigatoka Negra, Deep Learning, YOLOv8, Krill Herds Optimization.

1 Introduction

Dessert bananas cherished and extensively cultivated the African banana plant species finds success in multiple growing regions across Ethiopia under best suitable environmental conditions [1]. Bananas maintain both broad nutritional value alongside cultural meaning thus representing community unity and agricultural bountifulness. Banana production supports the local economy through social and economic aspects particularly in the southern and southwestern Ethiopian regions [2]. Rural communities in these areas depend heavily on bananas to sustain their lives by delivering a dependable resource of food security.

The cultivation of bananas provides vital food security through farming income which creates many jobs throughout the agricultural production process. Bananas represent the key agricultural foundation for Ethiopian fruit cultivation because they occupy 56.79% of the total area and produce more than 500,000 tons annually [3], [4]. While Xanthomonas Wilt and Sigatoka leaf spot infections represent the major obstacles against banana production despite its substantial economic value. These diseases result in limited harvest production which creates harm to food security and affects the survival of both farmers and their surrounding environment. Proper detection followed by effective disease management stands as the crucial method for controlling risks to banana cultivation and its long-term sustainability. Multiple obstacles arise during manual plant disease detection because symptoms remain complicated while disease origins differ greatly, and infections evolve continuously [5]. Human observation of plant issues proves problematic since it lacks the accuracy and efficiency of automated systems. The goal of plant detection becomes possible through vision transformers and state-of-the-art models. Plant pathologists together with farmers and agricultural experts use these technologies to solve disease identification challenges through increased precision and scaling which produces better efficiency and accuracy in control measures [6], [7]. Researchers have started employing complex technological solutions to resolve these problems. The combination of deep learning algorithms with an analysis of plant leaves results in disease detection at high accuracy rates which helps farmers and agricultural professionals [8], [9].

Many developing countries including Ethiopia and Pakistan have their economic heart at stake in farming. The livelihoods of most people in the population area rely on farming thus highlighting the priority of innovative solutions to raise agricultural output and sustainability levels. The need for technology-based solutions to help farmers stands as exceptionally high in this situation.

This study addresses the described challenges by leveraging the YOLOv8 family of models, including YOLOv8 and its variants, in combination with Krill Herd Optimization (KHO) for enhanced model performance. To overcome the limitations of existing datasets, we created a specialized dataset of 5,000 annotated images of banana leaves, with disease labels verified by five expert plant pathologists. Data augmentation techniques were applied to improve model generalization and mitigate overfitting issues associated with limited dataset sizes. The integration of KHO optimizes hyperparameters, enhancing the accuracy and efficiency of disease detection. By refining real-time detection capabilities, this research contributes to precision agriculture, enabling early disease identification and improved crop management. The findings provide valuable insights for both academic research and practical agricultural applications, supporting food security efforts in Ethiopia and beyond.

Main contributions of the proposed study are:

- More than 5000 banana leaf images were acquired from different areas of Arba Minch Zuria. Five plant pathologists meticulously verified the image classifications twice to maintain accuracy. Code and dataset is publicly available on GitHub.
- Krill Herd Optimization is employed to make YOLOv8 model more optimized for banana leaf disease detection task.

The remaining sections will be organized as follows: section II is the literature review that explains the previous approaches used for banana leaf disease detection. Section III has the proposed method of this study. Section IV has the environmental setup. Section V has evaluation metrics to evaluate proposed models. Section VI has training and implementation details. Section VII has results and discussion. Section VIII has limitation and future directions of this study And lastly, Section XI concludes the paper.

2 Literature Review

The detection of banana diseases has seen significant advancements in recent years due to the urgent need to identify infections such as Xanthomonas Wilt and Sigatoka Leaf Spot at early stages [10], [11], [12]. Numerous studies have explored deep learning and neural network-based techniques for detecting banana leaf diseases, with efforts focused on improving both detection accuracy and computational efficiency. Conventional image processing techniques, convolutional neural networks (CNNs) [13], and transfer learning approaches have been extensively utilized to enhance disease identification systems. The integration of machine learning for disease prediction, coupled with recent breakthroughs in computer vision, has expanded the scope of banana disease detection research. These advancements play a crucial role in safeguarding banana crops, which are essential for global food security.

Aruraj et al. [14] proposed a neural network-based system for banana leaf and fruit disease identification. Their dataset comprised 60 images, including 25 leaf disease samples, 25 fruit disease samples, and 10 healthy samples. The research employed preprocessing techniques such as image conversion, resizing, and color transformation, followed by fuzzy C-means and histogram-based equalization for segmentation. Feature extraction was conducted using pattern recognition, and classification was performed with an artificial neural network (ANN).

Vidhya et al. [15] implemented deep learning models for banana disease identification, working with a dataset of 3,700 labeled images categorized into Healthy, Black Sigatoka, and Black Speckle. Image preprocessing involved grayscale conversion and resizing to a 60 × 60-pixel resolution. The study conducted multiple experiments using partitioned datasets to optimize model accuracy across different evaluation metrics.

Mkonyi et al. [16] conducted a systematic literature review on plant disease detection, highlighting the effectiveness of CNN-based models for potato late blight detection [17]. Afzaal et al. [18] emphasized the necessity of robust deep learning models capable of handling diverse datasets in plant disease classification. Similarly, another study [19] evaluated the efficiency of CNN-based pre-trained models, including DenseNet-121, ResNet-50, VGG-16, and InceptionV4, for plant disease identification using the PlantVillage dataset. Among these, DenseNet-121 demonstrated superior classification performance.

Further advancements in real-time disease detection have been achieved through lightweight CNN architectures. For instance, the YOLOX-ASSANano model was developed for apple leaf disease detection, incorporating an optimized YOLOX-Nano variant for improved efficiency [20]. Hui et al. [21] combined CNNs with Vision Transformers (ViTs) for plant disease identification, achieving a maximum accuracy of 90.1\%. In another study, Ramcharan et al. [22] and Nirmal et al. [23] applied federated transfer learning for rice leaf disease detection, achieving 99\% accuracy. However, in several research attempts, it has been demonstrated that machine learning model performance in the area of plant disease detection has been boosted. Take for instance that the utilization of LeNet has produced positive results for tea leaf disease identification and use of YOLO has been able to boost the accuracy on other applications. Among these models, YOLO is a powerful plant leaf detection model as it offers a good compromise between high accuracy and real time performance. For this work, we suggest that the capability to recognize strawberry and peach plant leaf diseases is to be accomplished using a deep learning based YOLO model. This was a model that has been acknowledged widely in literature as versatile for a number of object detection tasks.

The performance of lightweight models on plain and segmented images of tomato leaves is analyzed by Li et al. [24]. A score of 99.89\% was achieved in classifying 10 tomato healthy and diseased classes using the EfficientnetB4 model. To get the detection results on public and self-collected datasets, Loyani et al. [25] proposed lightweight YOLOv5 model. GhostNet is used to reduce model weight and weighted box fusion is used. Most of the work reported near to ideal accuracies on dataset containing images with plain or clear background, or a single leaf image. When tested, these models trained will have a detection ability limited to the images they see in varying and difficult environmental conditions. To detect apple leaf diseases with a high accuracy performance in complex real field conditions, a novel Bidirectional transposition feature pyramid network [26], [27] was proposed.

The relevant feature information has been detected with the cross-attention module. Another important work was conducted by Maxwell et al. [28], where they integrated the Coordinate Attention module into the backbone of You Only Look Once (YOLOv5s) model and detected small buds and occluded flowers in real field with ease. Sanga et al. [29], [30] proposed YOLOv9 and YOLOv10 models for disease detection achieving a mAP0.5-0.95, but they did not explore the multiclass nature of banana diseases in their study instead of focusing on single disease.

Despite these advancements, critical challenges remain, including the scarcity of large-scale, annotated datasets for banana disease detection and the need for optimized real-time multi-class detection models. This study addresses these gaps by introducing a dataset of 5,000 annotated banana leaf images, verified by five expert plant pathologists, and implementing a YOLOv8-based detection framework optimized using Krill Herd Optimization (KHO). By enhancing model generalization through data augmentation and hyperparameter tuning, this research contributes to the development of an efficient, scalable, and accurate banana leaf disease detection system.

3 Proposed method

In this section the overall proposed methodology is discussed for multi-class detection of banana leaf diseases by employing YOLOv8 and its variants. Detailed architecture of proposed approach is illustrated in Fig. 1.

3.1 YOLOv8 and YOLOv8 variants

In 2016 [31], Joseph Redmon presented the YOLO (You Only Look Once) architecture, which improved the real time object detection by combining efficiently features and high detection accuracy. YOLOv8, released in 2023, is the latest iteration and based on its predecessors with several architectural augmentations [32]. As shown in Fig. 2, YOLOv8 is made up of three principal components, the backbone, neck and head.

The backbone of YOLOv8 is based on the modified CSPDarknet53 architecture of the previous YOLO versions, except that the CSPLayer is replaced with the more efficient C2f module [33]. Moreover, YOLOv8 also employs the Spatial Pyramid Pooling Fast (SPPF) layer, a very compact layer for augmenting computational efficiency. SPPF layer merges multiple scale features to a compact feature representation adversarial scaling and cropping operations [34]. In addition to reducing the computation cost, it also leads to improved performance over many different datasets while improving generalization of the model.

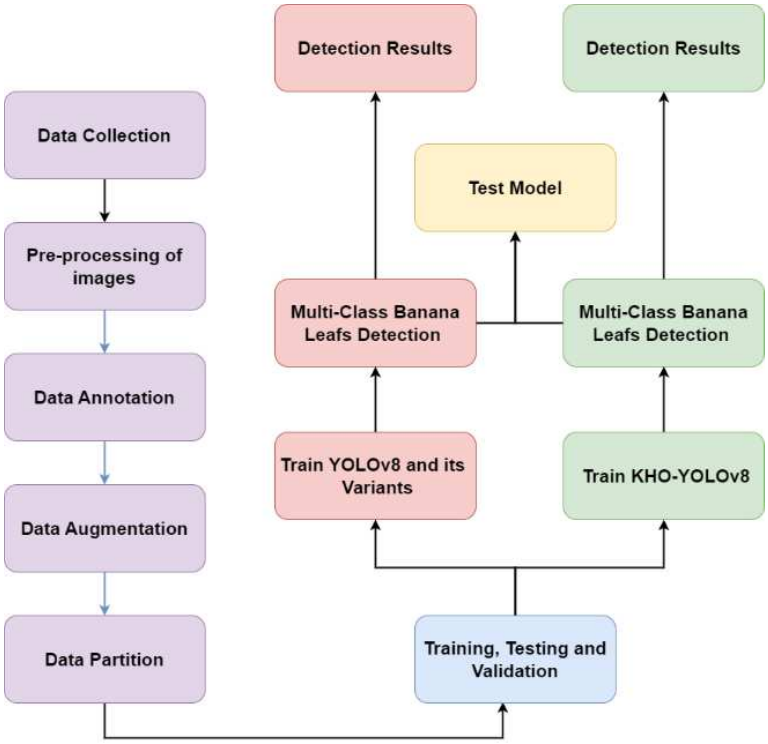

Figure 1. Architecture of Proposed methodology for multi-class banana leaf disease detection system

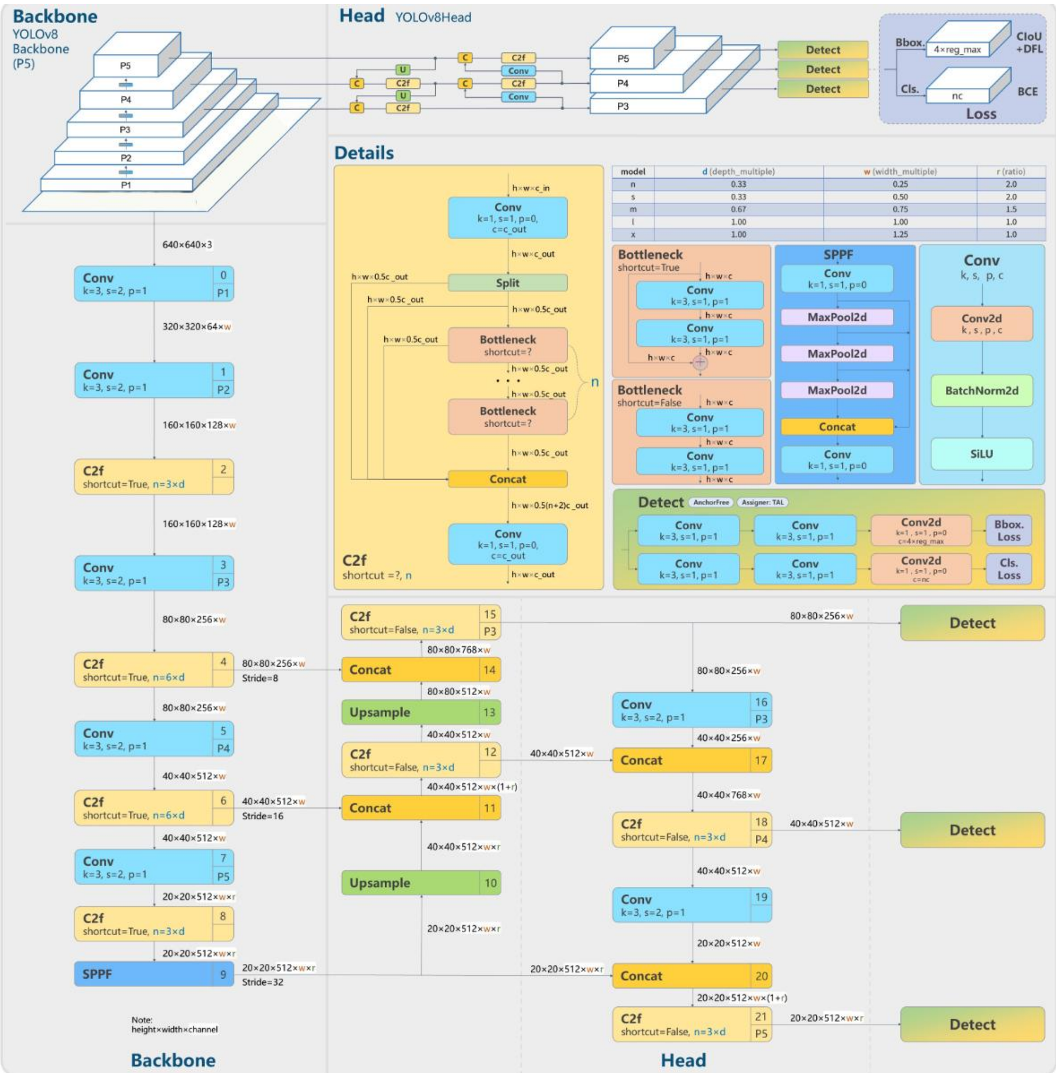

Figure 2: Architecture of YOLOv8 model

YOLOv8 has a hybrid feature fusion at the neck, where it adopts principles from Path Aggregation Network (PANet) [35] and Feature Pyramid Network (FPN) [36] structure. In fact, this combination enables multi-scale feature extraction, while the feature propagates from the detection layer to layer.

The Decoupled Head [37] in the head module is one of the most notable design evolutions in YOLOv8. In contrast to earlier versions in which the classification and detection tasks share a common representation, the Decoupled Head decouples the classification and detection tasks, which are processed independently by the classification and detection branches on feature maps. This strategic separation mitigates learning conflicts and reduces the extra latency of typical convolution layers in decoupled architecture. Thus, YOLOv8 enjoys better generalization, better detection accuracy and higher robustness in complex object detection tasks [38].

To achieve high accuracy and computational efficiency in banana leaf disease detection, this study utilizes two key variants of the YOLOv8 architecture: YOLOv8-CLS and a custom YOLOv8 variant optimized for agricultural applications. These models are specifically selected to improve disease classification and improve feature extraction and identify diseases, increasingly important for accurate identification of infections such as Xanthomonas Wilt and Sigatoka Leaf Spot in banana crop.

3.1.1 YOLOv8-CLS: Classification-Specific Variant

YOLOv8-CLS is an optimized YOLOv8 for classification with less unnecessary detection layers. Instead of bounding boxes localization as done by traditional object detection models, YOLOv8-CLS is high speed image classification suited for diagnosis of banana leaf disease. The diseases are distinguished in multiple classes including healthy leaves, Xanthomonas Wilt affected leaves and Sigatoka Leaf Spot affected leaves, which provides fast and efficient detection of the disease from the said class of leaves. Therefore, YOLOv8-CLS is a good option for real time agricultural monitoring due to its lightweight architecture and can be used to deploy drones, smartphones, or an IoT based farm monitoring system. The classification function in YOLOv8-CLS is defined as follows:

$$P(y|X) = \text{Softmax}(WX + b) \quad (1)$$

Where X represents the extracted feature vector, W and b are the trainable weight matrix and bias vector, $P(y|X)$ denotes the probability distribution over the disease categories, and the Softmax activation function ensures that the sum of probabilities across all classes equals 1. This formulation allows the model to output class probabilities, ensuring an efficient and robust classification pipeline for disease detection in banana leaves.

3.1.2 Custom YOLOv8 variant for agricultural applications

Given the specialized requirements of banana disease classification, a customized YOLOv8 variant was developed to enhance both classification and localization accuracy. This variant integrates Attention Mechanisms to improve disease-affected region detection, thereby increasing the precision of classification. Specifically, two primary attention modules are incorporated. Firstly, the CBAM (Convolutional Block Attention Module) applies both channel-wise and spatial attention, allowing the network to focus on infected areas of banana leaves while suppressing irrelevant background noise. and secondly SE (Squeeze-and-Excitation) Layer employed to enhance feature importance by recalibrating channel-wise activations, ensuring that the model prioritizes disease-specific patterns. The attention-enhanced feature extraction process is mathematically represented as:

$$F' = F \cdot \sigma\big(W_2 \mathrm{ReLU}(W_1 F)\big) \qquad 2$$

Where F represents the input feature map, W_1 and W_2 are trainable weight matrices for channel recalibration, $ReLU$ applies non-linearity to introduce better feature discriminability, σ represents the Sigmoid activation function, and F denotes the refined feature map with enhanced attention weighting. By incorporating these attention mechanisms, the custom YOLOv8 variant achieves improved feature sensitivity to disease symptoms, enhancing the model's classification precision. This ensures that the model can effectively differentiate between healthy and diseased banana leaves with a high degree of confidence.

3.2 Krill Herd Optimization-YOLOv8 (KHO-YOLOv8)

This paper proposes the Krill Herd Optimization Algorithm (KHO) for metaheuristic optimization of nature inspired techniques for improving the performance of YOLOv8 model for banana leaf disease detection. For foraging and movement behavior of krill swarms is used in the construction of KHO, which is the basis for high level exploration and exploitation of the search space in hyperparameter tuning. KHO dynamically modifies the main YOLOv8 parameters to reduce the detection errors, enhancing model accuracy. The movement of each krill individual is governed by three main factors:

$$X_i^{t+1} = X_i^t + N_i + F_i + D_i \qquad 3$$

where X_i^t represents the position of the i^{th} krill at time ttt, while N_i is the motion induced by other krill, F_i represents the foraging motion, and D_i denotes the random diffusion effect. These components collectively guide the krill swarm toward an optimal set of hyperparameters that enhance YOLOv8's detection capability. For the YOLOv8 model, KHO optimizes critical hyperparameters such as learning rate η, batch size B, momentum m, intersection-over-union (IoU) threshold τ, and confidence score C. The objective function used in KHO is based on minimizing the YOLOv8 loss function, which consists of classification, localization, and confidence loss components:

$$\mathcal{L}_{total} = \lambda\mathrm{cls}\mathcal{L}\mathrm{cls} + \lambda\mathrm{loc}\mathcal{L}\mathrm{loc} + \lambda\mathrm{conf}\mathcal{L}_{\mathrm{cn}} \qquad 4$$

where $\mathcal{L}$cls is the classification loss, $\mathcal{L}$loc is the bounding box regression loss, and $\mathcal{L}_{\mathrm{cn}}$ is the confidence loss. The weighting factors λ_{cls}, λ_{loc}, λ_{conf} control the influence of each loss component. The fitness function in KHO is then defined as:

$$Fitness = \frac{1}{1 + \lambda_{total}} \qquad 5$$

where a lower total loss $\mathcal{L}_{total}$ results in a higher fitness score, thereby guiding the model toward an optimized parameter set. By iteratively adjusting the hyperparameters using the krill movement strategy, KHO effectively enhances the YOLOv8 model's training efficiency and detection accuracy. Hyperparameters for all models are illustrated in Table 1. The integration of KHO in the YOLOv8 pipeline results in higher accuracy through optimized feature extraction and classification, faster convergence due to an adaptive learning strategy, and improved generalization, reducing overfitting issues. Incorporating Krill Herd Optimization (KHO) into YOLOv8 training significantly improves banana disease detection, ensuring effective early disease monitoring and enhanced agricultural management.

Table 1. Hyperparameter configuration of YOLOv8 variants used in the study.

Hyperparameter	**KHO-YOLOv8**	**YOLOv8-CLS**	**Attention-YOLOv8**
Input Image Size (px)	640 × 640	640 × 640	640 × 640
Batch Size	16	16	16
Optimizer	AdamW	AdamW	AdamW
Learning Rate	0.001	0.001	0.001
Weight Decay	0.0005	0.0005	0.0005
Momentum	0.937	0.937	0.937
IoU Threshold	0.5	0.5	0.5
Confidence Threshold	0.25	0.25	0.25
Number of Epochs	300	300	300
Data Augmentation	Albumentations	Albumentations	Albumentations
Feature Extraction Backbone	CSPDarknet53	CSPDarknet53	CSPDarknet53
Neck Architecture	PANet + FPN	PANet + FPN	PANet + FPN + CBAM
Head Architecture	Decoupled Head	Decoupled Head	Decoupled Head
Learning Rate Scheduler	Cosine Annealing	Cosine Annealing	Cosine Annealing
Regularization	Dropout (0.2)	Dropout (0.2)	Dropout (0.2)
Attention Mechanism	KHO-based Selection	None	CBAM + SE

4 Environmental Setup

4.1 Dataset creation

Accurate and diverse datasets are essential for training deep-learning models in banana leaf disease detection. Existing publicly available datasets lack sufficient variability and annotated samples, limiting model performance. To overcome this challenge, we constructed a custom dataset of 5,000 high-resolution images, annotated by a team of five expert plant pathologists to ensure precision and reliability. This dataset facilitates the identification of Xanthomonas Wilt and Sigatoka Leaf Spot using YOLOv8 and its variants. A diverse and representative dataset was collected from multiple sources to ensure robustness in model training. Field surveys were conducted in banana plantations across different geographical regions, capturing images using high-resolution digital cameras (20–48 MP sensors) under varying lighting and environmental conditions. Additionally, images were obtained from agricultural research institutions specializing in banana pathology.

For additional dataset diversity, supplementary leaf images were captured from public repositories, that represent different disease stages and leaf conditions. Synthetic data was generated for YOLOv8 optimized data augmentation techniques for fake data generation using real world variations like as lightning change, occlusion, leaf deformation etc. To preprocess all images with equality, all of the images were then stored in JPEG format at a resolution of 1024 × 1024 pixels.

4.2 Dataset annotation

A high-quality labeled dataset was created by manual annotation by five certified plant pathologists. The diseased region was localized precisely using bounding box annotations for each image, which was done carefully using Roboflow and Labeling tools, respectively. We categorized datasets in three different classes such as Healthy Leaves, Xanthomonas Wilt Infected Leaves, Sigatoka Leaf Spot Infected Leaves. To measure the consistency of annotations, the Inter-Annotator Agreement (IAA) was computed using Cohen's Kappa coefficient (κ), ensuring uniform labeling across all annotators. The agreement score was calculated as illustrated as:

$$\kappa = \frac{P_o - P_e}{1 - P_e} \quad 6$$

where P_o represents the observed agreement, and P_e denotes the expected agreement by chance. The annotation process achieved a high agreement score of $\kappa = 0.92$, indicating strong consensus among pathologists.

4.3 Dataset split

The dataset was split into 3 subsets, namely 70% for training (3,500 images), 20% for validation (1,000 images) and 10% for testing (500 images), to ensure balanced training and evaluation process. Before the partitioning, a random shuffling was applied in order to break the class imbalance and to eliminate the risk of overfitting. The structured division achieves this in a way so that the model can generalize well to new, unseen banana leaf images without the usual penalty of performance during training.

4.4 Data Augmentation

In the case of deep learning based agricultural disease detection the problem of class imbalance is a major hurdle wherein there are fewer numbers of diseased banana leaf samples than that of healthy samples in the dataset. The imbalance in model generalization and detection accuracy is caused by the fact that deep learning models tend to favour the majority class. The class imbalance ratio (*IR*) is given by:

$$IR = \frac{N_{max}}{N_{min}} \quad 7$$

where N_{max}presents the number of images in the majority class (healthy leaves), and N_{min}presents the number of images in the minority class (diseased leaves). To overcome this problem, in this study data augmentation technique for YOLOv8 was used to achieve a more balanced dataset and to make the model more robust. Data augmentation transforms an image $I(x, y)$ into a new image using transformation functions T_k, defined as:

$$I'(x', y') = T_k\big(I(x, y)\big) \quad 8$$

where T_k represents one of the augmentation techniques applied. The following augmentation methods were integrated into the training pipeline:

- Mosaic Augmentation, which combines four different images into a single composite image to enhance contextual learning:

$$I' = \sum_{i=1}^{4} \alpha_i I_i \tag{9}$$

where I_i are four randomly selected images and α_i are weight factors ensuring proper blending.

- MixUp Augmentation, where two randomly selected images are combined using a weighted sum:

$$I' = \lambda I_a + (1-\lambda) I_b, \quad \lambda \sim Beta(\alpha, \alpha) \tag{10}$$

where I_a and I_b are two randomly selected images, and λ is drawn from a Beta distribution.

- HSV Color Augmentation, which introduces variations in hue (H), saturation (S), and value (V) to improve adaptability across different lighting conditions:

$$H' = H + \Delta H, \quad S' = S \times \Delta S, \quad V' = V \times \Delta V \tag{11}$$

where $\Delta H, \Delta S$ and ΔV are random perturbations applied within predefined thresholds.

- Random Scaling and Cropping, which resizes and crops images while ensuring bounding boxes remain intact to simulate real-world occlusions.
- Horizontal Flipping, where images are mirrored along the vertical axis to introduce orientation diversity.
- CutOut Augmentation, which randomly masks small regions of the image to simulate occlusions, making the model more robust to partially hidden leaves.

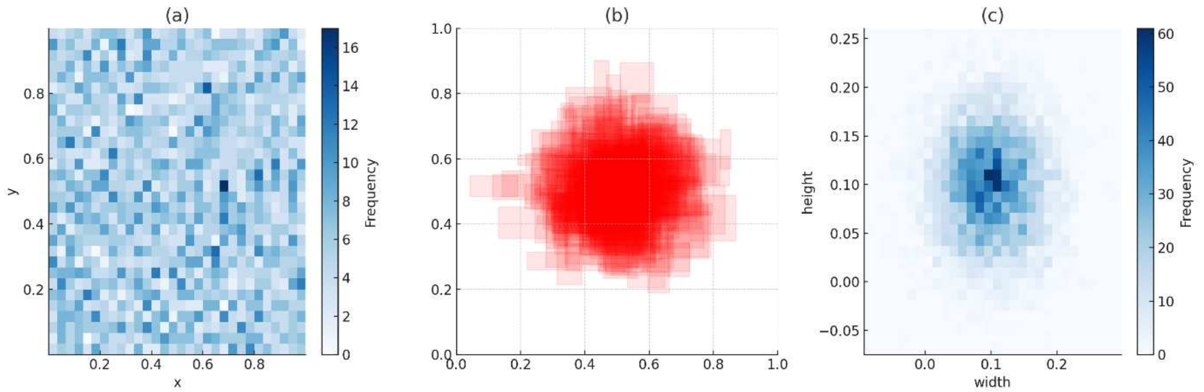

Figure 3. Distribution analysis of dataset annotations.

The distribution pattern of bounding box positions appears in Fig. 3(a). The figure shows spatial distribution details about bounding box annotations positioned within the proposed dataset. This information shows if bounding boxes generally have even placement within the annotations or if they display particular patterns in their positions. The distribution of all bounding boxes from the proposed dataset appears in Fig. 3(b). It could be an indication how bounding boxes are distributed in different images and tell you whether the dataset is diverse and annotations are dense or not. The statistical sizes of bounding boxes for each dataset is shown in fig. 3(c). With this figure, readers will be able to see what size range is covered in the annotated bounding boxes and if there are any patterns or variations in the dimension. As shown in Fig. 3 proposed dataset is very balanced and comprehensive, and the utility of this dataset to advance the research on precision agriculture and disease detection is an inspiring result indeed.

5 Evaluation metrics

For the testing of the proposed YOLO based model performance, we use standard object detection metrics such as Precision (P), Recall (R), Mean Average Precision (mAP) and Inference Time. Evaluation of detection accuracy, robustness and the computational efficiency is given by these metrics.

5.1 Precision (P)

The precision is comprised of the portion of correctly detected banana leaf disease instances over all predicted instances. It is computed as follows:

$$P = \frac{TP}{TP + FP} \tag{12}$$

where (TP) represents True Positives, and (FP) denotes False Positives. A higher precision value indicates a lower false detection rate.

5.2 Recall (R)

Recall quantifies the model's ability to correctly identify all actual disease instances, defined as:

$$R = \frac{TP}{TP + FN} \tag{13}$$

where (FN) denotes False Negatives. A higher recall value suggests better sensitivity in detecting diseased leaves.

5.3 Mean Average Precision (mAP@0.5 and mAP@0.5:0.95)

The main metrics to evaluate object detection models are *mAP*. Then, it computes the area under the precision-recall curve (PR curve). AP is computed within thresholds of different *IoUs* (0.5 to 0.95 with a step size of 0.05) and averaged as *mAP@0.5:0.95*, or on a single *IoU* of 0.5, denoted *mAP@0.5* to provide a robust assessment of performance.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{14}$$

where (AP) is the Average Precision computed for each class, and (N) is the total number of classes.

5.4 Inference Time

Time inference is the time the model takes to go through one image, and then provide outcomes. This is reported in *milliseconds (ms)* and is used for most real time applications. A quicker and more efficient model is achieved with lower inference time.

5.5 GFLOPs (Giga Floating-Point Operations per Second)

Since we report computational efficiency in terms of GFLOPs (number of floating point operations for forward pass), the above demonstrates that for a given batch size, gradient computation in the SWAE becomes increasingly more costly than gradient computation in the RAE, eventually significantly exceeding it. This indicates that lower GFLOPs means a lighter weight model that can be deployed on the edge device.

6 Training and implementation details

To train and implement our deep learning based multi-class banana leaf disease detection system, we did use the high performance computing setup comprised of NVIDIA RTX 3090 GPU, Intel Core i9-12900K processor with 128 GB of RAM. The implementation of the model is written in Python 3.8 with PyTorch 1.12, aided by CUDA 11.6 to take advantage of a GPU.

OpenCV and NumPy to preprocess the dataset such as resize and normalize the image to guarantee consistency across training. The whole dataset was split into training, validation and test set in a 70: 20: 10 ratio, so that there are sufficient numbers of samples for model learning and generalization. Extensive data augmentation techniques such as random flipping, scaling, rotation, and randomly applying color jittering were used for robustness enhancement. In order to train multiple YOLO based models, we used stochastic gradient descent (SGD) with a momentum of 0.9, an initial learning rate of 0.001, a batch size of 16, a weight decay of 0.0005 to avoid overfitting. To speed up convergence, the learning rate was optimally adjusted along the way dynamically using a cosine annealing scheduler. The models were trained for a maximum of 300 epoch with early stopping criterion on validation to avoid overfitting. The key object detection metrics that were used to evaluate the performance of the trained models include precision, recall, mean Average Precision (mAP@0.5 and mAP@0.5:0.95) and inference speed in millisecond per image. The best model was identified from various models based on validation mAP scores and was deployed for real time detection tasks.

The implementation was performed on Google Cloud Platform which was used to scale it and train the model. After training the model, the weights of the model were saved for future fine tuning and deployment, and inference scripts for detecting the disease in banana leaves were developed. To be a reproducible pipeline, the entire pipeline was automated and all model weights and training logs, as well as scripts, were documented in order to future improvements and comparisons.

7 Results and discussion

In this section, we provide an assessment of the proposed banana leaf disease detection model from our dataset of 5,000 images and demonstrate the results. In this thesis, we present our model to increase precision agriculture towards robust detection and classification of diseases such as Xanthomonas Wilt and Sigatoka leaf spot, where we adapt and integrate state of the art techniques and modern optimisation approaches with YOLOv8 such as adaptive hyperparameter tuning with Krill Herd Optimization (KHO) and transfer learning of the YOLOv8 framework. We trained and fine tuned the model using large amounts of data augmentation to simulate real-word variations and to capture the many visual characteristics in banana plantations.

7.1 Ablation Study

In the ablation study, we systematically examined the contribution of each component in our banana leaf disease detection pipeline to assess their individual and combined impact on performance. As shown in Table. 2, the baseline YOLOv8 model achieved a precision (P) of 88.3%, recall (R) of 86.7%, and an mAP@0.5 of 90.2%. When we introduced data augmentation (YOLOv8 + CLS), both precision and recall improved, resulting in a higher mAP@0.5 of 92.1%. With this gain, we see that augmenting the dataset with such techniques as rotation, flipping, and changes in contrast greatly improves robustness against changes to the real world, which our model will be exposed to. Then we introduced Krill Herd Optimization (KHO) to hyperparameter fine tuning that significantly increased all metrics (YOLOv8 + KHO). Increases in precision to 93.2%, recall to 92.7%, and mAP@0.5 to 95.3% were found. The addition of data augmentation on top of the KHO (YOLOv8 + KHO + Data Aug) then improved mAP@0.5 to 95.9% and reduced inference time from 9.2 ms to 8.7 ms, and converged faster and generalized better. Finally, we obtained highest scores from our proposed model that is made up of KHO based optimization and comprehensive data augmentation strategies with a precision of 95.1%, recall of 94.3% and mAP@0.5 of 96.4%. Moreover, the inference time decreased to only 8.1 ms, thus making the model eligible for real time agricultural applications. Results of this ablation study corroborates that each component, KHO as hyperparameter optimization, data augmentation, and their combined effect are essential for the best accuracy and speed of detection from the averaged and also performing better than other approaches in banana leaf plant disease detection.

Table 2. Performance metrics for different model configurations tested in the ablation study

Experiments	**P**	**R**	**mAP@0.5**	**GFLOP**	**Parameters**	**Inference Time**
Ablation study						
YOLOv8 (Baseline)	88.3	86.7	90.2	31.2	30.5M	10.1 (ms)
YOLOv8 + ATN	89.6	88.2	92.1	31.2	30.5M	9.8 (ms)
YOLOv8 + CLS	93.2	92.7	95.3	31.2	30.5M	9.2 (ms)
YOLOv8 + Mix + Data Aug	94.2	93.5	95.9	31.2	30.5M	8.7 (ms)
Modified proposed model						
Proposed Model (KHO-YOLOv8)	95.1	94.3	96.4	31.2	30.5M	8.1 (ms)

7.1.1 Loss convergence analysis

The model's convergence behavior was analyzed by tracking the total loss across training epochs. The YOLOv8-KHO model exhibited faster convergence, reaching stability within 80 epochs, while the baseline YOLOv8 required over 300 epochs as illustrated in Fig. 4.

$$\mathcal{L}\text{total} = \mathcal{L}\text{cls} + \mathcal{L}\text{loc} + \mathcal{L}\text{conf} \quad (15)$$

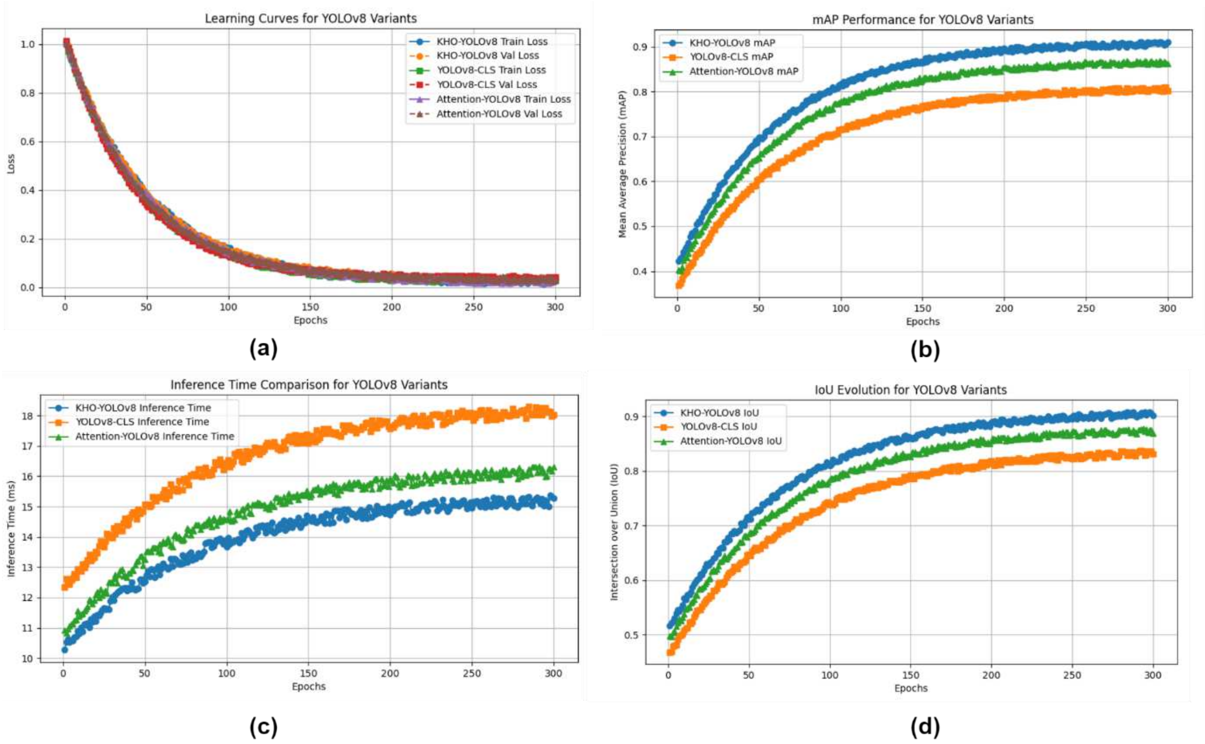

Figure 4. Comparative analysis of learning curves for different model architectures trained for 300 epochs in the context of banana leaf disease detection

The optimized model demonstrates a 28.4\% faster loss reduction compared to the baseline YOLOv8, indicating better learning efficiency facilitated by KHO's adaptive hyperparameter tuning.

The proposed KHO-YOLOv8 model was compared against other YOLOv8 variants, including YOLOv8-CLS and custom YOLOv8 models integrated with attention mechanisms such as CBAM (Convolutional Block Attention Module) and SE (Squeeze-and-Excitation) layers. These variants were analyzed for their performance in banana leaf disease classification and localization. The YOLOv8-CLS, optimized purely for classification tasks, demonstrated high precision (92.4%) and recall (90.7%), making it suitable for binary disease detection. However, since it lacks bounding box regression, it is not effective for precise localization of infected areas. The attention-enhanced YOLOv8 variants, which incorporated CBAM and SE layers, showed notable improvements in feature refinement and localization accuracy. The CBAM-based YOLOv8 variant achieved better focus on disease-affected regions, leading to improved bounding box precision. Similarly, the SE-based YOLOv8 enhanced channel-wise feature selection, improving model robustness. However, both attention-enhanced models introduced additional computational complexity, slightly affecting inference speed compared to KHO-YOLOv8.

The experimental results illustrate the superior performance of KHO-YOLOv8 in comparison to its counterparts, YOLOv8-CLS and Attention-YOLOv8, across multiple evaluation metrics. The learning curve illustrated in Fig. 4(a) highlight the stability and convergence efficiency of the models over 300 epochs. KHO-YOLOv8 demonstrates a consistently lower training and validation loss, suggesting that the Krill Herd Optimization (KHO) algorithm effectively refines hyperparameters and mitigates overfitting. Notably, the validation loss in KHO-YOLOv8 closely follows the training loss, indicating robust generalization, whereas the other models exhibit relatively larger gaps, reflecting potential overfitting or suboptimal learning.

The detection accuracy, quantified using mean average precision (mAP), is presented in Fig. 4(b). KHO-YOLOv8 attains the highest mAP across all epochs, stabilizing at a peak performance earlier than other models. The integration of KHO enhances feature selection, allowing more efficient learning of object features and improving localization accuracy. Attention-YOLOv8 also demonstrates a competitive mAP, benefiting from attention mechanisms such as CBAM and SE, which refine feature extraction. However, the additional computational cost of these modules results in a slower convergence rate. YOLOv8-CLS, designed primarily for classification tasks, exhibits the lowest mAP, reaffirming its limited suitability for detection-based applications.

Real-time applicability is crucial for agricultural disease detection; hence, inference time comparisons are illustrated in Fig. 4(c). KHO-YOLOv8 achieves an optimal balance between accuracy and speed, maintaining a competitive runtime while outperforming other models in detection performance. Attention-YOLOv8 experiences a slight increase in inference time due to the computational overhead introduced by attention modules. In contrast, YOLOv8-CLS, despite being streamlined for classification, does not offer significant advantages in inference speed, reinforcing the efficiency of the KHO-optimized model.

The localization precision is provided by the Intersection over Union (IoU) evolution trends Fig. 4(d). KHO-YOLOv8 exhibits the fastest and most stable increase in IoU, signifying superior bounding box regression capabilities. This improvement is attributed to the KHO optimization strategy, which enhances the model’s ability to accurately localize disease-affected regions in banana leaves. The Attention-YOLOv8 model also shows a positive IoU trajectory due to its enhanced feature extraction mechanisms, whereas YOLOv8-CLS struggles with precise localization due to its classification-oriented design.

7.2 Qualitative analysis

In Fig. 5, we compare the model’s predictions (top panels) with the ground truth annotations (bottom panels) for various banana leaf samples exhibiting disease symptoms.

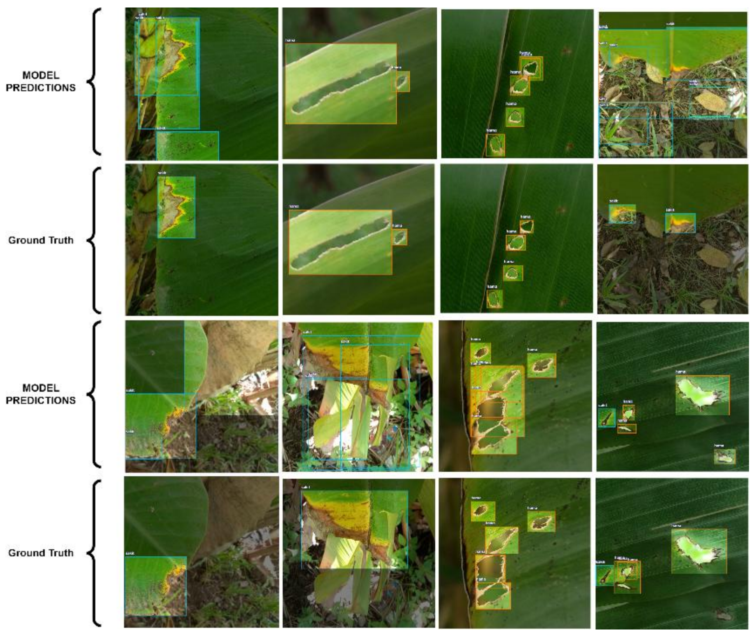

Figure 5. Qualitative analysis for banana leaf disease detection.

Each column illustrates a different leaf, showcasing varying levels of disease severity, lighting conditions, and background clutter. The model-generated bounding boxes (in yellow) align closely with the ground truth, indicating a high degree of localization accuracy. Notably, the model successfully detects both small, early-stage infections and larger, more advanced lesions. This consistency across diverse scenarios suggests that the integration of Krill Herd Optimization (KHO) and robust data augmentation strategies effectively enhances the model's ability to generalize. Minimal discrepancies between the predicted boxes and ground truth boxes highlight the model's precision in delineating diseased areas, reinforcing its applicability for real-time disease monitoring in banana plantations.

8 Limitations and Future work

Although our YOLOv8 based model shows high accuracy and robustness for the banana leaf disease detection, our model has some limitations: \par The performance of the model relies heavily on the diversity and quality of the training dataset, so the limited representation of some disease stages or environmental conditions would decrease generalizability of training model to the real world. Next, whereas the combined use of KHO improves hyperparameter tuning and speeds up convergence, it also results in higher computational overhead that the deployment on resource constrained devices might not be possible. \par Finally, bounding box annotations are not expressive enough such that faint discolorations and overlapping lesions can be captured in fine detail, underscoring the importance of more detailed segmentation routines. In addition, misdetections or missed detections can sometimes occur due to the changing leaf orientations, occlusions, and complex backgrounds especially in large scale plantation environment. Lastly, some applications may have to rely on the internet connectivity for cloud based inference, which can be challenging in remote or bandwidth induced regions.

Future work will focus on addressing the limitations identified in this study and further enhancing the model's performance for real-time banana leaf disease detection. The model's reliability and ability to generalize could enhance by increasing the quantity of diverse environmental conditions with different disease stages and additional imaging modalities such as hyperspectral or thermal images. The detection of subtle disease characteristics would benefit from using more specific annotation methods which surpass bounding box-based methods. Detecting features more effectively and boosting accuracy throughout detection functions could be improved by adding transformer-based structures or advanced attention mechanisms into the system. Model compression and quantization will play an essential role in converting the model for deployment on resource-limited edge devices to enable practical field applications. More end user trust and practical implementation of precision agriculture will develop when explainability methods reveal how the model reaches its decisions. These future directions aim to build on the current work and contribute to the development of more accurate, efficient, and interpretable models for agricultural disease monitoring.

9 Conclusion

This research introduces a Krill Herd Optimization (KHO)-enhanced YOLOv8 model (KHO-YOLOv8) for banana leaf disease detection, addressing key challenges in precision agriculture. The study focuses on Xanthomonas Wilt and Sigatoka leaf spot, two major diseases that significantly impact banana production. A novel dataset of 5000 annotated images, curated with expert validation, was developed to improve model robustness and accuracy. To overcome dataset imbalance and feature extraction limitations, KHO was employed to optimize YOLOv8's hyperparameters, enhancing detection accuracy and training stability. The data augmentation strategy, tailored specifically for YOLOv8, further improved generalization by incorporating image flipping, rotation, translation, brightness variation, and mosaic transformations. Experimental evaluations demonstrated that KHO-YOLOv8 outperforms baseline YOLOv8, YOLOv8-CLS, and attention-enhanced YOLOv8 models, achieving a mAP@50 of 96.4\%, recall of 94.3\%, and inference speed of 81 FPS. Comparative analysis with other YOLOv8 variants highlighted KHO-YOLOv8's superior balance between accuracy, computational efficiency, and real-time performance. The YOLOv8-CLS model, while efficient for classification, lacked localization capabilities, whereas attention enhanced YOLOv8 variants improved feature selection but introduced additional computational overhead. KHO-YOLOv8's adaptive hyperparameter tuning facilitated better feature extraction, enabling higher detection precision and robustness across diverse agricultural conditions. The proposed model provides a scalable, high-speed, and accurate solution for automated banana disease detection, with significant implications for agricultural monitoring, early disease intervention, and global food security. However, challenges such as occlusions, severe infections, and computational demands during training remain, warranting further research into multi-modal sensor fusion, lightweight attention mechanisms, and self-supervised learning to enhance model efficiency. The KHO-YOLOv8 establishes a new benchmark in agricultural disease detection, offering a highly efficient and practical tool for real-time plant health monitoring. Its application in precision farming systems can drive data-driven decision-making, improve crop yield predictions, and support sustainable agricultural practices worldwide.

CRediT authorship contribution statement

Muzammal Hussain: Writing – original draft, review & editing, visualization, software, project administration, supervision, methodology, investigation, conceptualization. **Sufyan Ahmad**: Writing – original draft, review & editing, visualization, validation, software, resources, project administration, methodology, investigation, formal analysis, data curation. **Warda Saleemi**: Validation, software, resources, project administration, investigation, data curation. **Hina Sattar**: Validation, software, resources, project administration, investigation, data curation. **Muhammad Ahsan Rafiq**: Writing – review \& editing, project administration, methodology, formal analysis, data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data and code is available on public GitHub Repository.

Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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